, IN, June 10-12, 1987

LEARNING CONTROL FOR ROBOTIC MANIPULATORS WITH SPARSE DATA

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ABSTRACT

Learning control algorithms have been proposed for error compensation in repetitive robotic manipulator tasks. It is shown that the performance of such control algorithms can be seriously degraded when the feedback data they use is relatively sparse in time, such as might be provided by vision systems. It is also shown that learning control algorithms can be modified to compensate for the effects of sparse data and thereby yield performance which approaches that of systems without limitations on the sensory information available for control.

INTRODUCTION

Robotic manipulators typically have highly nonlinear dynamics and are often subject to substantial dynamic disturbances due to such factors as unmodelled dynamics, variable joint frictions, and unknown payloads. These factors can result in unacceptable errors in manipulator motions. To reduce these, a number of advanced control algorithms have been proposed (1,2). Unfortunately such algorithms can require extensive calculations, and do not exploit a very important aspect of commercial manipulators: namely that most robot tasks are repetitive.

Recently, a class of control algorithms, called learning control, has been developed which utilizes this repetitive nature to compensate for these error sources. These algorithms require less calculations than many other advanced control algorithms. Learning control algorithms also do not depend on accurate detailed dynamic models of the manipulator which may be hard to obtain.

Learning control algorithms were originally proposed by Uchiyama in 1978 (3). A number of algorithms of this type have been developed since. Although different names are used, like "learning control" and "repetitive control", the algorithms tend to be similar. Learning control algorithms have been presented in the continuous time domain (4) and in the discrete time domain (5) and have been shown to perform well both analytically and experimentally (6,7).

In the studies of learning control algorithms to date, it has been assumed that the errors used by the algorithms can be measured continuously along the manipulator's path. However, in many potential applications, such as those using vision, the error signal can be measured only at relatively few points along the path. This condition is referred to here as a sparse data case, and it is shown that the sparseness of the data will degrade the performance of the learning controller. Although the work presented in this paper used Togai's learning controller (5) as its basis, the sparse data control techniques developed here can be applied to other learning controllers as well.

In this paper, three methods are presented which are shown to reduce the errors introduced by the sparseness of data available to learning control algorithms. They were each tested by simulation for two system.

THE SYSTEMS

A one degree of freedom (DOF) single link device (representing a linear system), and a three degree of freedom SCARA-type manipulator (representing a nonlinear system) were used (Figure 1). A complete description of these systems and their dynamic equations of motion are contained in reference (8).

To design the learning controller, the nonlinear dynamic equations for the SCARA were linearized. Conventional proportional-derivative (PD) controllers were designed as the "local controllers" (shown in Figure 2) used in conjunction with the learning control algorithms. The PD-controller's parameters were selected to approximate a second order system response with natural frequency of 18 radians per second and a damping ratio of 0.9 in the case of the single link system. The SCARA's local controller was design to approximate a third order system with similar transient characteristics (8). It should be noted that the feedback to the local controller is continuous.

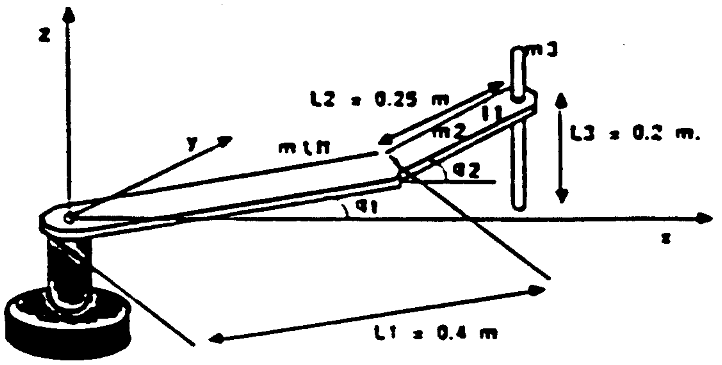

Figure 1. SCAPA Type Three DOF Nonlinear Manipulator

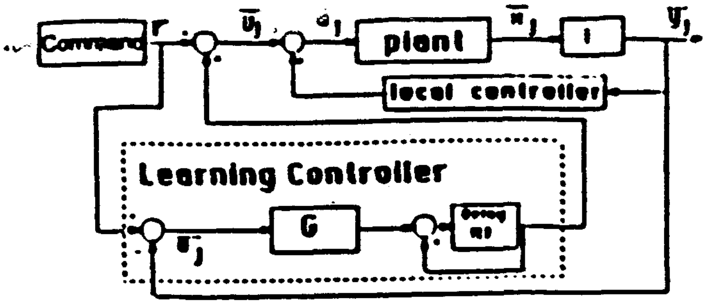

Figure 2. Learning Control Block Diagram.

THE BASIC LEARNING CONTROL ALGORITHM

Basically, a learning controller learns the behavior of a system from the errors generated during a given cycle of the system. It uses them in the next cycle to add a correctional (learning) signal to the command so that the tracking error decreases. The learning signal at a specific point on the manipulator path during any cycle is a cumulative function of the errors at that same point during all the previous cycles. Hence, the learning signal can be thought of as a series of integrators, one for each point on the path.

Figure 3 shows the basic learning algorithm used in this study, see reference (5). It can be described as follows:

$$\underline{v}_{j+1}(k) = \underline{v}_j(k) + G\underline{e}_j(k+1)$$

$$\underline{e}_j(k) = \underline{r}(k) - \underline{x}_j(k)$$

where j : j^{th} cycle

k : k^{th} sampling point on the path

$\underline{v}$ = input to the plant and local controller

$\underline{e}$ = the error

$\underline{r}$ = the command = $\underline{v}_0$

G = the learning gain matrix

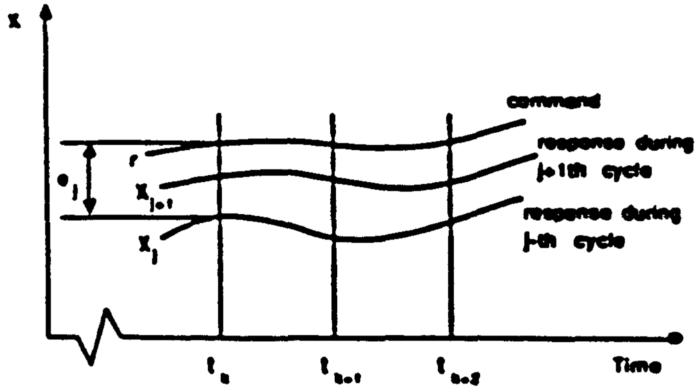

Figure 3. Response With Learning Control.

The results obtained in this study show that a properly designed learning control algorithm without limitations on its data, non-sparse learning, performed well for both the linear single link system and the nonlinear SCARA. However, as the sparseness of the feedback data increases, the performance of the learning controller degrades.

Figure 4 shows the first four cycles of the single link system with learning control. The command consists of a series of ramps and dwells. Here the learning controller used a relatively large number (40) of measurements per cycle (MPC). This is close to the non-sparse case. Since the learning control algorithm does not affect the system's response during the first cycle, this cycle's response shows the system behavior without learning. In Figure 4, this first cycle's response deviates quite substantially from the command. The learning controller clearly forces the system response to converge to the command as the system repeats its motion; it learns successfully.

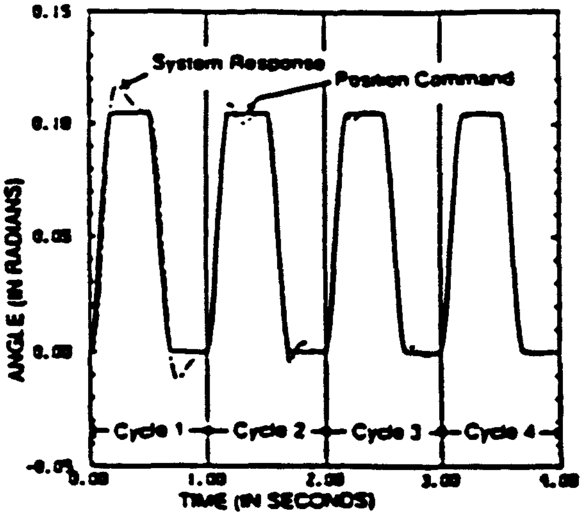

Figure 4. Single Link Non-Sparse Learning.

The system's response with sparse learning control (8 MPC) is shown in Figure 5. Here the system's response does not converge in later cycles to its desired profile. This figure shows the important degrading effect that sparseness of the measured signal can have on the system's performance. The degradation of the system's performance as a function of the number of MPC is shown in Figure 6. Here the RMS value of the error, taken over each cycle, is plotted for various measurement rates. Clearly, as the number of measurements decreases, the error tends not to converge toward zero.

The correlation between performance and the number of measurements used by the learning algorithm for the nonlinear SCARA robot parallels the single link results. Figure 7 shows the SCARA tip position error rapidly decrease over several cycles for 40 MPC. For this case the manipulator is commanded to move its end effector back and forth between the points (0.20, 0.25, 0) and (0.372, 0.750, 0.1) along a straight line (see figure 2). The commanded distance along the path is a harmonic function of time with a frequency of 2.5 Hz. There is a 0.05 second dwell at the end of each move. When the measurements becomes more sparse, the errors increase, see Figure 8.

The objective of this study was to develop methods to improve the performance of learning controllers under sparse data conditions. Some of the techniques considered are discussed below.

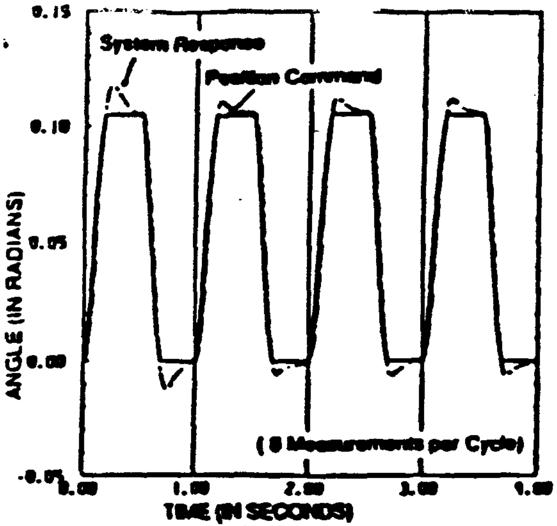

Figure 5. Sparse Learning.

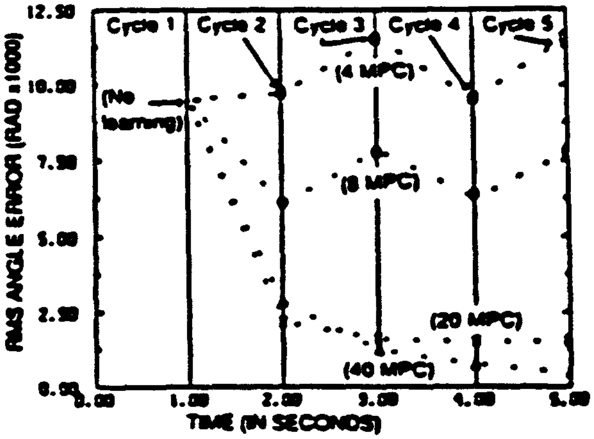

Figure 6. Single Link System RMS Error.

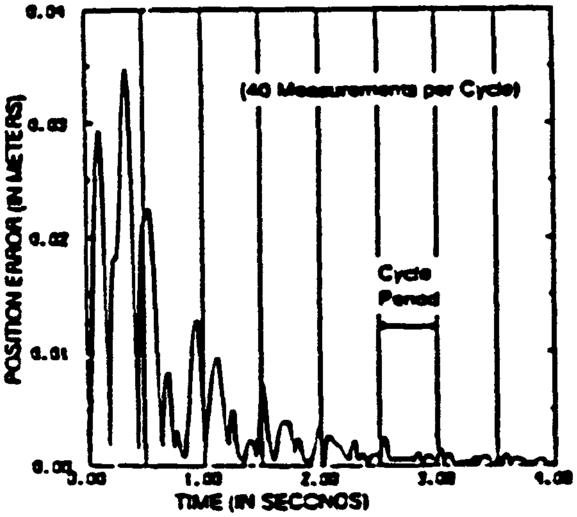

Figure 7. SCARA Error for Non-Sparse Learning.

LEARNING CONTROL ALGORITHMS FOR SPARSE DATA

A Data Shift Algorithm

One method for improving the performance of the learning controller, given a limited amount feedback data which can be obtained in one cycle, is to shift the location of the measurement points slightly in each cycle. The error can be measured at many path points during a period of several (n) cycles. The algorithm does not act upon these measurements until after the end of the n-th cycle. This improves convergence, but it will be n times slower.

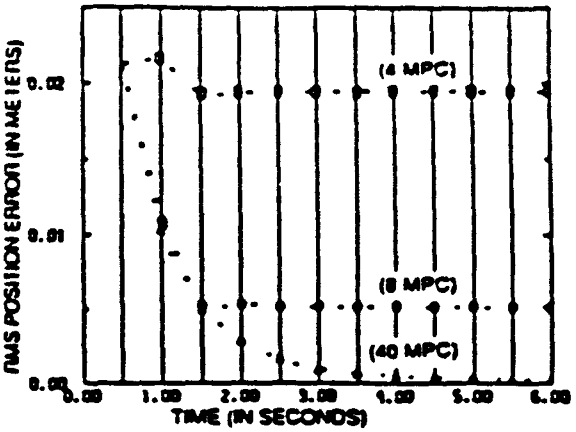

Figure 8. SCARA RMS Tip Error for Sparse Learning.

The technique's effectiveness as applied to the single link system, is shown in Figure 9. Here the link was driven by a 2.5 Hz sinusoidal command. The error was measured in five cycle groups and at a rate of 4 MPC. During this time, the measurement location within a cycle is shifted as described above. Every five cycles the information is used to correct the system response. The improved performance is quite dramatic, as shown in Figure 9. The final error is essentially zero. The results presented in Figure 6 indicate, that for 4 MPC, the basic learning controller without data shift would give a rather large residual error. These results show how this technique improves the steady state error, but greatly increases the number of cycles required to achieve the correction. This can be a problem in some cases.

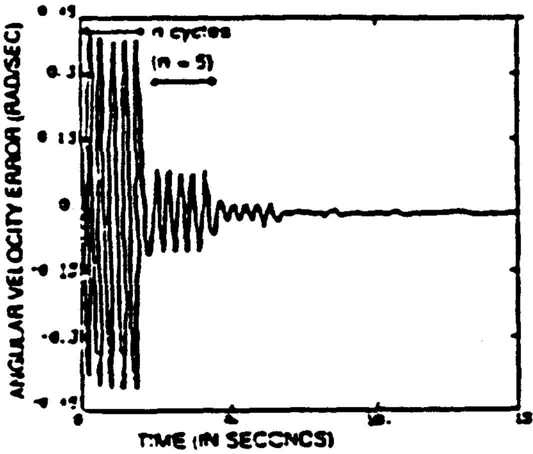

Figure 9. Single link Sparse Learning with Data Shift Learning (Velocity).

Forward Estimation Learning

A second method studied to decrease the apparent sparseness of the feedback data without sacrificing the speed of convergence, was to use a system model and state information from actual measurements to estimate the error at points where no measurements are made. Using the state of a previous point (whether measured or estimated) and a linearized system model, expressed in standard state space form, it is possible to integrate forward in time and estimate the error at a point further along the path, by the equation:

$$\hat{\underline{x}}_j(k+1) = \hat{A}\hat{\underline{x}}_j(k) + \hat{B}\underline{v}_j(k)$$

where, "^" indicates estimated values. The estimation error (where "~" indicates "error") is given by:

$$\tilde{\underline{x}}_j(k+1) = \hat{\underline{x}}_j(k+1) - \underline{x}_j(k+1)$$

$$= \tilde{A}(k)\underline{x}_j(k) + \tilde{B}(k)\underline{v}_j(k) + \hat{A}(k)\tilde{\underline{x}}_j(k) - \underline{w}_j(k)$$

The first two terms $\tilde{A}(k)\underline{x}_j(k)$ and $\tilde{B}(k)\underline{v}_j(k)$ are due to modeling errors. The third term is due to the estimation error at the previous sampling point. The final term represents the unmodelled disturbances. These equations were used to obtain measures of the anticipated accuracy of the learning controller with estimation.

In the analysis of the learning algorithm it was assumed that the value of $\underline{w}_j$ does not change much from one cycle to the next; i.e. $\underline{w}_{j+1}(k) = \underline{w}_j(k)$ (e.g., frictions at similar points are almost same). Furthermore all the state variables are assumed to be available at the measurement points.

The forward estimation technique worked well to improve the performance of the learning control algorithm with sparse data for the single link system. Figure 10 shows a large error for this system at 4 MPC (for a sinusoidal input). It also shows the good performance that can be achieved at 20 MPC. Nearly identical performance is obtained when only 4 points per cycle are measured and 16 points per cycle are estimated with no modelling errors. Clearly the learning control algorithm with estimation, where the estimator has exact knowledge of the system's parameters, is every bit as good as the system which uses an equivalent number of measured points. The figure also shows the performance of the estimating algorithm when the values for the effective link inertia used by the estimator were substantially in error (by 11 %). The results for this case show that the algorithm continued to perform well, because the linear form of model still matched the linear equations of the actual system. However the algorithm did not perform as well when it was applied to the nonlinear SCARA robot.

Simulations for the SCARA showed a significant decrease in its performance when forward estimation was added. In these cases the estimator used a simple linear model and was clearly not beneficial. An estimator with a nonlinear model was not considered, because it would not be consistent with the traditional learning control approach not to rely on complex nonlinear models. If one is willing to use such models it can be argued that more direct computed torque control methods (9) should be applied rather than learning control.

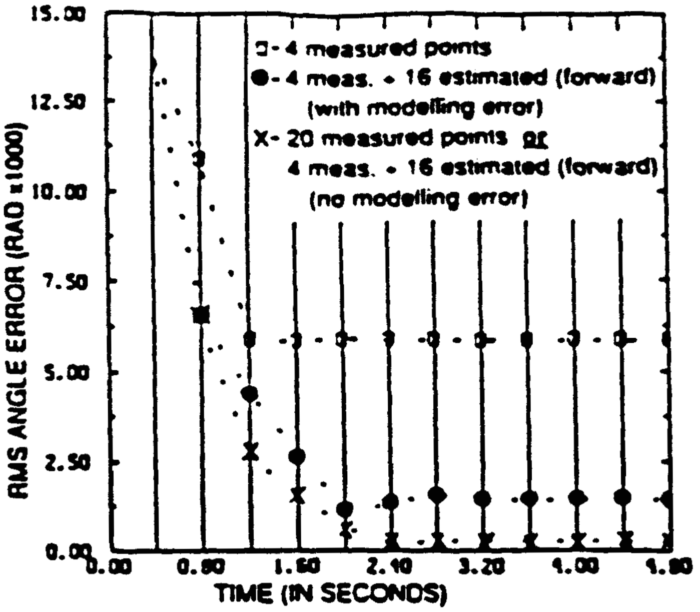

Figure 10. Single Link Estimation Learning.

Forward & Backward Estimation Learning

A third method uses both forward and backward estimation and is less sensitive to modelling errors. Backward estimation is possible because the learning controller does not use the information that it gathers during a cycle, until the next cycle. Figure 11 shows how two measurements are used to obtain an estimate at a point in between. The forward estimation algorithm uses both $\underline{x}_j(k)$ and $\underline{x}_j(k+2)$ to estimate the value of $\underline{x}_j(k+1)$. Both estimated values of $\underline{x}_j(k+1)$ are then averaged.

The estimation is given by:

$$\hat{\underline{x}}_j(k+1) = [\hat{A}\underline{x}_j(k) + \hat{B}\underline{v}_j(k) + \hat{A}^{-1}\underline{x}_j(k+2) - \hat{A}^{-1}\hat{B}\underline{v}_j(k+1)] /2$$

Under certain conditions backwards integration can lead to numerical instabilities, and techniques have been developed that consider these problems (10). Since the estimation errors caused by modelling errors and disturbances tend to cancel with each other on average, the estimation error is smaller than that of the previous estimation method.

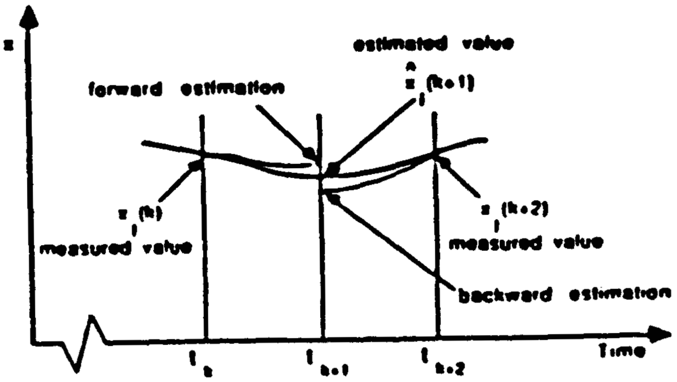

Figure 11. Single Link Forward/Backward Estimation Learning.

The application of this approach to the single link, with modelling errors of 11%, is shown in

Figure 12. It shows the performance for the case without estimation (10 MPC), the case with only forward estimation (10 MPC, and 10 estimated points), and the case with 10 MPC, and 10 estimated points using the forward and backward averaging estimation technique. The forward estimation method reduces the important final RMS error to approximately one half of those without estimation. The forward and backwards technique further reduces the error by more than half to less than 20 percent of the non-estimation steady state error. These results indicate that the linear model based forward-backward estimation technique works very well for the linear single link system with errors.

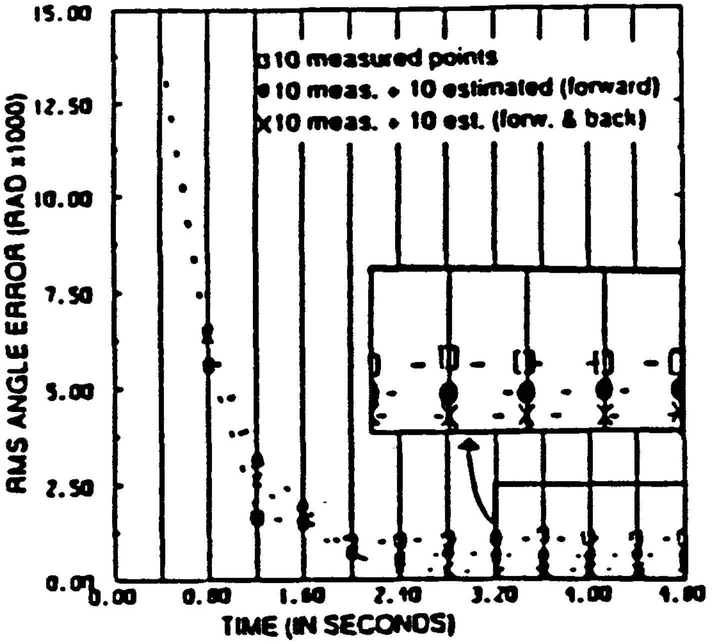

Figure 12. Single Link Forward/Backward Estimation Learning, with Modelling Errors.

However, as discussed earlier, the forward estimation algorithm did not perform well when it was applied to the nonlinear SCARA robot, in fact it increased the steady state RMS error. Figure 13 shows that the forward-backward estimation learning does significantly better for the SCARA. In this figure, the perfomance for 20 MPC learning without estimation is shown, along with forward and forward-backward estimation learning. The two estimation cases used 20 MPC and 20 estimated points per cycle. As before, the forward estimation case was worse than the case without estimaticn. However, the forward-backward estimation technique reduces the important steady state error by more than 50 percent. Results such as these suggest that the forward-backward estimation technique does tend to cancel the errors introduced by the use of a simple linear model to predict the performance of this nonlinear system.

CONCLUSIONS

It has been shown that in cases where the manipulator's errors can be measured only at relatively few points along its path, such as in systems using vision, the performance of the learning control algorithm that was studied, seriously degraded. In this study three methods were presented which were shown to substantially reduce the errors introduced by the sparseness of data available to learning control algorithms. The presented results suggest that these techniques can effectively reduce the errors of learning control algorithms introduced by data mesurement limitations. The work also showed that the nonlinear characteristics of manipulators can, in certain cases, decrease the effectiveness of these techniques and that future research in this area is necessary.

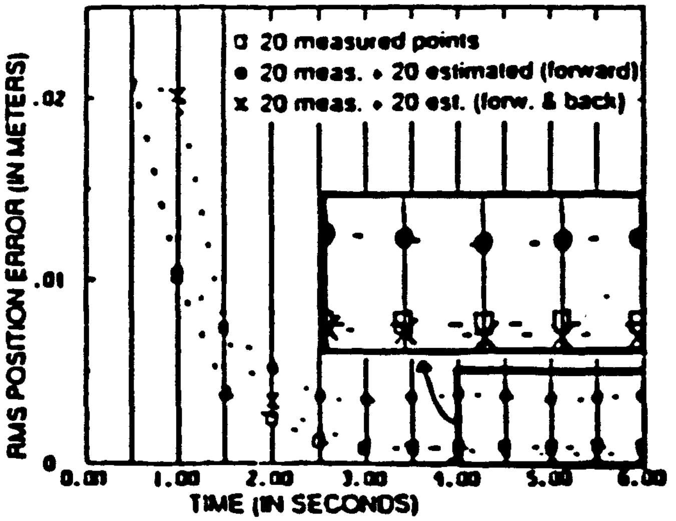

Figure 13. SCARA Forward/Backward Estimation Learning, with Modelling Errors.

ACKNOWLEDGEMENTS

This work was supported by the Automation Branch of NASA Langley Research Center under Grant NAG-1-489. The authors would also like to acknowledge Mitsubishi Electric Corporation for supporting A. Morita's work at MIT.

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